Investigating Weather Shocks and the Farmers' Perceptions of Climate Change in the American Farmland Market

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Abstract

U.S. agriculture is likely to be affected by climate change due to its inherent reliance on climatic inputs. An important difference among methods of climate change impact assessment is the treatment of farmer adaptation. This study posits that farmers must perceive the climate is changing as a prerequisite of engaging in adaptive strategies. I test this by exploiting the effect of random weather fluctuations on farm real estate. A theoretical model clarifies how weather shocks could affect farmland values, in which I consider farmers as Bayesian learners. I then rely on a distributed lag model to test the hypothesis. The results suggest that farmers do not perceive recent extreme weather as indications of sizable upcoming changes in farm profitability. I find no evidence that weather shocks have affected the farmland market. These findings are robust to geographic and temporal subdivisions.

Introduction

Agriculture is arguably one of the most researched sectors in the climate change impacts literature (Ortiz-Bobea, 2013). Over the last three decades, statistical and econometric approaches have become increasingly popular among economists in contrast to earlier biophysical process counterparts.[1] Significant disagreement persists in terms of the sign and magnitude of such impact on the agricultural sector (Fisher, Schlenker, Haneman, and Roberts, 2012).

This disagreement derives from the various ways in which economists model farmer adaptation to climate change, resulting in serious disparities. The climate change impact literature has progressed from explicitly limiting farmer adaptation (via the production function and crop simulation method) to implicitly assuming the farmer has adapted to their current climate (via the Ricardian method) and recently modeling farmer adaptation in response to weather shocks or assuming that the farmer is forward-looking.

Despite these advances and improved usages of observational data to estimate the hypothetical impact of a change in climate on agricultural production or society's welfare, there is still a gap in the literature: the modeling of whether or not a farmer perceives (believes) that the climate has changed. I therefore construct an additional test to explore if farmers' perceptions of their local climate has been changing.

To be more explicit, I rely on a long panel of county-level farmland values from the U.S. Census (1950 - 2012) and on detailed weather data from Schlenker and Roberts (2009) to develop a distributed lag model.[2] This model allows me to investigate if a farmer's perceptions of weather is based on not only present day experience, but on recent past experiences as well. I part from previous methods that have modeled farmers as forward-looking, by constructing a panel of survey and fine-scale weather data, where causality is

[1] Much of the economic literature suggests that in the short term, producers will continue to adapt to weather changes and shocks. In the longer term, however, these adaptive strategies will likely no longer buffer producers and/or consumers from significant welfare loss (Hatfield et al., 2014).

[2] It should be noted that this study is not a damage study.

based on weather shocks. Although the usage of survey data to model farmers' perceptions of climate change is not new, by restricting my sample to only include the agricultural census and not an aggregate of surveys, I mitigate the issue of extrapolating farmers' perceptions from that of public opinion.

Moreover, I argue that by choosing to measure changes in farmland value over changes in crop yields, I will more easily be able to detect if changes in our dependent variable are reflective of a change in the farmer's perceptions, and not worry about disentangling the biological response from the behavioral one, which would be imperative, were I to use crop yields.

This study contributes to the literature on adjustment costs where the farmer is assumed to be a Bayesian learner. Thus from a policy perspective, this study provides a template to measure the price signal that weather shocks have on farmland real-estate, and provides clarification on whether or not a market failure has occurred, in which case government intervention is justified.

Literature Review

Methods to model the perceptions regarding climate change have included stated preference and revealed preference approaches. Those that have utilized the former have oriented their analysis around stated preference survey results. However, there are no recurrent surveys that include the agricultural sector's perceptions of climate change in the United States.[3] And of those surveys that do target this stakeholder group, the scope is limited, and results can be difficult to interpret. For instance, Arbuckle et al.(2013) find that although Iowa is one of the states where temperature has changed the least in recent years, 65% of the study's farmers in a recent survey indicated that they believe that "climate change is occurring" but only 35% of them were concerned about the impacts of climate change on their farm operation.

An alternative approach to answer the question of whether farmers think the climate is

[3] These include the annual Gallup Environmental Survey, the Yale Project on Climate Change Communication, and the National Survey of American Public Opinion On Climate Change.

changing is to rely on farmer-revealed preferences, which are implicitly embedded in observational data. With farm real estate representing much of the value of the U.S. farm sector assets, economists have sought to understand how weather and climate impact the farmland market by conducting land value studies, where the value of land is equal to the present discounted value of the future stream of profits that could be generated with a given parcel of land (Nickerson et al., 2012). The theoretical foundation for nearly all of these studies is based on either the net present value (NPV) method or the hedonic pricing method. Below, a brief overview of the empirical strategies is reviewed.

The seminal paper by Mendelsohn, Nordhaus, and Shaw (1994) – hereafter MNS (1994) – introduced the Ricardian approach, in which the economic impacts of climate change on U.S. agriculture were estimated with a hedonic method. This novel approach consisted of a cross-sectional regression of land values on historical climate variables. Previous methods to measure the economic impact of climate change on agriculture assumed farmers had a limited range of adaptation strategies to adopt.[4] MNS (1994) implicitly assumed the opposite: a farmer has full selectivity of adaptation strategies to employ. The chief concern of the Ricardian approach is that it is likely that these estimates suffer from omitted variable bias due to collinearity between climate variables and time-invariant unobservables (Schlenker, Hanemann, and Fisher, 2006; Deschênes and Greenstone, 2007; Fisher, Hanemann, Schlenker, and Roberts, 2012).

The comparison of climate change impact estimates through the inclusion and omission of control variables is one method to mitigate and detect time-invariant omitted variable bias. Two prominent control variables found in climate change impact literature are irrigation and potential land development. Each has been empirically shown to significantly influence farmland. Plantinga et al.(2002) find that farmland close to urban areas inflates land values, because of the option value of land for urban development. Concluding that the

[4]The earliest and most comprehensive studies to estimate the impacts of climate change on agriculture were via the production function approach (see Adams, 1989; Kaiser et al.,1993). This approach examined the effect of weather on specific crop yields.

highly subsidized price of irrigated water and its uncertain future availability biases pooled estimates, Schlenker,Hanemann, and Fisher (2005) emphasize the importance of accounting for irrigation in the Ricardian model.[5] The usage of control variables does not inform us of the strength of the collinearity between climate variables and unobservables, and as such it is not a definitive solution to time-invariant omitted variable bias (Ortiz-Bobea, 2016).

More recent studies have shifted from a cross-sectional to a panel method approach to address this time-invariant omitted variable bias, and the relationship between agricultural output and weather variation. Instead of long-run climate averages being the explanatory variables of interest, year-to-year changes in temperature, precipitation, and other climatic variables tend to become the focus. The usage of weather shocks to isolate impact of climate variables on agriculture is a specific type of panel method approach that has strong identification properties. Using exogenous variation in weather outcomes over time (and within a given spatial location), this approach has the power to causatively identify the effects of weather variation on agricultural output. A risk of using this approach is the inclusion of time-varying observables. Although the inclusion of these can absorb residual variation, the empiricist can still run into the omitted variable bias problem, and the over-controlling problem that also complicates the cross-sectional approach (Dell et al., 2014; Hsiang, 2016).[6]

The continued debate on how climate change will impact agriculture can in part be attributed to how these revealed-preference studies have reflected adaptation in their theoretical and empirical application. Adaptation in climate change literature signifies the changing of one's behavior in response to or in expectation of some climatic phenomena, so that damages from said phenomena are minimized or the positive benefits are maximized (Tol et al., 1998).

An assumption in the Ricardian literature is that farmers have adapted to their local

[5]In their study, Schlenker, Hanemann, and Fisher (2005) define an irrigated county is one where at least 20 percent of said county's harvested cropland is irrigated. Those counties with less than 20 percent of irrigated farmland are referred to as dry counties.

[6]Hsiang (2016) notes that time-varying omitted variable bias arises if there are (important) time-varying factors that influence both the outcome and are correlated with climate variables, after being conditioned.

climatic conditions. This implies that they are exhibiting profit-maximizing behavior. However, behavioral decision research over the last 40 years provides a series of lessons about the importance of affect in perception of risk and in decisions to take actions that reduce or managed perceived risks. There is evidence from this field of research which suggests that worry drives risk management decisions (Weber, 2006). Hence if a farmer fails to be alarmed about a change in the climate or the risk it poses to them, they shall not take precautions.

How farmers perceive the risk of potential climate change to (their) agricultural productivity plays a significant role when it comes to empirically trying to deduce if farmers have had the foresight and have planned for said potential climate change. Shrader (2016) highlights the fact that a significant amount of what is known in terms of climate change impacts on the economy, stems from analysis where the adaptation is *ex post* to experienced weather. Alternatively, if we assume that the economic agent is forward-looking, an *ex ante* adjustment would be made in anticipation of climate change. A recent study by Severen et al.(2016) is firmly grounded on this concept that modern-day farmers take into consideration not only historical and current weather events, but make use of climate projections and other information sets that relay the message of warnings and climate change impacts.

This study contests that within the last thirty years, there has been a distinctive shift in the American agricultural sector, with evidence that farmers have been acknowledging that climate change exists, and is reflected as changes in farmland value. According to the authors, this shift in market behaviors corresponds to the proliferous amount of scientific publications in support of climate change that began in the 1990s, notably with the release of the first Intergovernmental Panel of Climate Change (IPCC) report and usage of the Hadley General Circulation Model (HGCM3). Severen et al.(2016) conclude that since 1987, the farmland market has been capitalizing the farmer's belief that the climate is changing.

The capitalization of potential future climate change in agricultural land value relates to a farmer's expectations of whether or not the climate is or will change. With significant levels of uncertainty about climate change, the usage of a Bayesian learning model provides a common foundation for modeling the updating of an individual's beliefs about future climate. As Lybbert et al.(2007) explain, people typically start off with an initial set of beliefs about the likelihood of a specific event occurring. These beliefs are consequently updated when they receive new information pertaining to that event. The power of this learning model resides in its ability to make inferences in the face of uncertainty (Kelly,Kolstad, and Mitchell, 2005; Deryugina, 2013).[7]

Yet for any given event, not all economic agents face the same level of risk and uncertainty. Hirshleifer and Riley(1992) illustrate how the confidence of an economic agent's prior belief can determine whether or not they receive new information in face of this uncertainty, and the impact that this information has on the updating of their beliefs.[8] Specifically, all else equal, the greater the confidence in their prior beliefs, a stochastic shock will be more impactful on their belief updating, relative to individuals who have less confidence in their prior.

The channels through which these weather shocks might affect farmland values is clarified by the theoretical model, below. The model posits that, with regard to their climate priors, farmers are Bayesian in their learning process, and this learning stems primarily from realized weather. Moreover, I show that it is the variance of weather realizations that modulates how long it takes for a farmer to realize that the weather has changed.

Theory

Capitalization Model

According to the United States Department of Agriculture (USDA), in recent years, farm real estate (land and structures) has typically accounted for about four-fifths of the total value of U.S. farm assets.[9] This farmland value embodies the discounted future streams of rent from that land, hence reflecting that farmer's expectations of future returns to that land.

[7]Criticisms of the Bayesian learning method with respect to climate change impact literature, include whether or not farmers are myopic, in which case farmers are not Bayesian learners.

[8]Confidence in this context can be understood as the tightness in the prior probability distribution.

[9]For more details on farmland real estate, see https://www.ers.usda.gov/topics/farm-economy/land-use-land-value-tenure/farmland-value.

By inserting farmland value into a capitalization model, we are able to understand how a change in local weather, a weather shock, will affect that farmland market. This is assuming that weather shock, which is somewhat discontinuous in space, is used as an exogenous source of variation in the farmer's prior belief about the local climate. Hence farmland value can be written in terms of a capitalization model as $L_{it} = \sum_{t=0}^{\infty} \frac{E[\pi_{it}]}{[1+r]^t}$.

The term L_{it} represents the value per acre of farmland for farmer i in period t, and is equal to the sum of expected discount future returns, E is the expectations operator conditioned on information available for farmer i at time t, r is the discount rate, and lastly π represents maximum profit. Let z_{it} represent the random variable of observed weather, where $z_{it} = [temperature_{it}, precipitation_{it}]$. Without loss of generality, suppose that weather is drawn from a normal distribution with mean μ and variance σ^2. A key component in determining how farmers process unusual weather events depends on how variable the underlying climatic distribution is. I define a measure of "precision" for observed weather as $\rho = \frac{1}{\sigma^2}$.

Considering that weather is a direct input for agricultural production, I can illustrate farmer's expected profit as the optimization problem:

$$\begin{aligned} E[\pi(z_{it}, p_{it}, w_{it}) = \underset{x_{it}, y_{it}}{\text{maximize}} \quad & p_{it} f(x_{it}, z_{it}) - w_{it} x_{it}] \\ \text{subject to} \quad & y_{it} = f(x_{it}, z_{it}) \end{aligned} \tag{1}$$

where expected profit for i in time period t consists of three arguments: output prices p_{it}, input prices w_{it}, and observed weather z_{it}, respectively.[10] The term y represents a vector of agricultural output, while x is a vector of input variables. Furthermore, the farmer does not believe the distribution of weather has changed relative to the previous time period.

Bayesian Learning Model

Now consider the case where the distribution of weather changes, such that the true mean of weather shifts from $\mu \to \tilde{\mu}$. To simplify the exposition, I assume that climate change is affecting the mean weather, not the variance of weather, which the farmer knows, and experiences $z_{it} \sim \mathcal{N}(\tilde{\mu}, \sigma^2)$ each year (Burke and Emerick, 2016). Assume that a farmer

[10] Similar to Kelly, Kolstad, and Mitchell (2005), I assume that the input and output prices which the farmer faces are not affected by weather and remain constant.

has a prior belief about the mean weather at any point in time, $\theta(t)$. Let the initial prior θ_0 be based on historical record. Therefore in time period t, farmer i believes that $\mu_{it} \sim \mathcal{N}(\theta_{it}, \frac{1}{\gamma_{it}})$, where γ_{it} represents the farmer's precision (confidence) that $\theta_{it} = \tilde{\mu}_{it}$. If a farmer had full information about the change in climate, then $\gamma_{it} = \infty$ and the farmer's confidence in their prior belief of mean weather would be zero, leading them to quickly adapt.

In reality, however, farmers are likely to update their priors about the climate over time as changing weather patterns are realized, only modifying their behavior after obtaining strong enough information that the climate has changed. For example, suppose that the mean precipitation in May has increased by 4 inches. As the years go by, the farmer gradually changes his estimate of the mean precipitation. However, until the farmer is completely informed of the new precipitation, he will continue to lose profits as a consequence of making sub-optimal input and production decisions (Kelly et al., 1999). To model this change in the farmer's prior, I assume that the farmer follows a Bayesian learning process. This assumption provides us a template to model how economic agents update their beliefs in the face of uncertain events like changes in weather fluctuations.

According to Bayes rule, after the farmer observes $z_{i,t+1}$ (see Cyert and DeGroot, 1974; Kelly, Kolstad, and Mitchell, 2005), they will update their prior θ_{it} to generate the posterior $\theta_{i,T}$, where T represents time-periods. This posterior estimate is a weighted average of prior beliefs about mean weather and realized weather.

$$\theta_{i,T} = \frac{\gamma_{it}\theta_{it} + T\rho z_{it}}{\gamma_{it} + T\rho} \tag{2}$$

The weights associated with the farmer's prior and observed weather are γ_{it} and ρ, respectively. The term γ_{it} represents the farmer's confidence that their prior belief of mean is equal to the mean climate $\tilde{\mu}$. In contrast, ρ does not represent a confidence, but the variance of weather events. Note that the denominator in (2) represents the posterior precision after T years. Following Burke and Emerick (2016), I assume that this change in the mean is not accompanied by a change in the variance. Hence, I do not examine the evolution of how a farmer's confidence (γ_{it}) changes over time in the long term. Accordingly, I redefine the farmer's prior belief to be normally distributed and consisting of their prior belief of mean weather and the variance of observed weather, such that $\mu_{it} \sim \mathcal{N}(\theta_{it}, \sigma_i^2)$.

To reflect this updating in (2), I can revise expected profit to be equal to the following: $E[\pi(z_{it})] = \int \pi(z_{it}) N(\theta_{it}, \sigma_i^2) dz_{it}$. This formula states that the expected returns from observed weather are equal to the infinitesimal sum of the distribution of weather $\pi(z_{it})$, which represents the monetary value of observed weather, and $N(\theta_{it}, \sigma_i^2)$ which represents the density of the farmer's prior belief of the mean weather.

Connectivity between land value, expected profit, and a farmer's updating of prior beliefs is now hopefully evident to the reader. Taking the derivative of our expected profit equation with respect to weather and letting λ equal the discount factor of $\frac{1}{(1+r)^t}$, a change in land value after a weather shock can be written as:

$$\frac{\partial \lambda L_{it}}{\partial z_{it}} = \lambda \int \frac{\partial f(z_i t}{\partial z_{it}} \frac{\partial N(\theta_{it}, \sigma_i^2)}{\partial z_{it}} dz_{it} \tag{3}$$

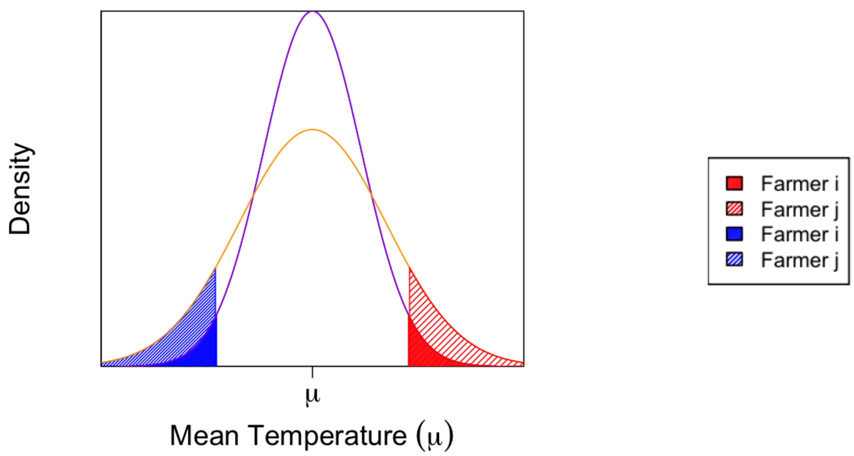
which states that a shock in observed weather leads to a change in land value through a change in discounted expected profit, integrated over all weather outcomes.[11]

A crucial point to highlight in (3) is the Bayesian learning process, which is embedded in θ_{it}. For illustrative purposes, let $t = 0$ demarcate the current time period and $t = 1$ represent the time period immediately after a weather shock. Referring to (3), the change in this prior after the weather shock is equal to $\frac{\partial \theta 1}{\partial z} = \frac{\rho}{\gamma_0 + \rho}$, which illustrates that the variance of weather modulates how a farmer's prior changes with a shock to weather.

Figure 1 provides a visual representation to better understand how a greater variance in the weather distribution can influence a farmer's recognition that the climate has changed. In Consider farmers in two neighboring counties i and j , where $\rho_{i0} < \rho_{j0}$. After a weather shock, *ceteris paribus*, then in the next time we can expect farmer j to receive a more impactful lesson from this weather shock. The curves in Figure 1 represent two competing

[11]Where a weather shock can be defined as a change in the distribution of observed weather.

states of nature – observed weather for farmer i (in purple) and observed weather for farmer j (in orange), but both experience mean weather centered at μ. The areas shaded in red represent exposure to extreme hot days, whereas the areas shaded in blue represent exposure to extreme cold days. The density of exposure to these extreme days is greater for farmer j than for neighboring farmer i. As such, after a weather shock, the type I and type II errors for farmer j are larger than the corresponding errors belonging to farmer i in part because of farmer j's larger weather variance. This translates into larger adjustment costs for farmer j.



Notes: This figure identifies how two farmers with different baseline climates, have different exposures to extreme hot (shaded in red) and extreme cold (shaded in blue) days. Notice that exposure to extreme days for farmer j is actually the combination of the two textures of the same color.

Figure 1: Theoretical Distributions for Two Farmers with Different Variances of Weather Realizations

Data

Sample Determination

In the agricultural economic literature, development pressure and agricultural irrigation are recognized to be two potentially important determinants of farmland value. As such, following Schlenker and Roberts (2006), I confine my sample to counties in the contiguous United States that are neither irrigated or urban.

Influence of Development Pressure

Noting that land prices reflect not only the current uses of land, but potential uses as well, Plantinga et al.(2002) find that over 80 percent of farmland value close to New York City is attributable to the option value of developing land for urban uses. Hence, the impact of weather shocks and climate change will likely have a different effect on urban land prices and surrounding farmland, than rural areas. Following the literature, a county is considered to be urban if it has population density greater than 400 persons per square mile.

Influence of Irrigated Farmland

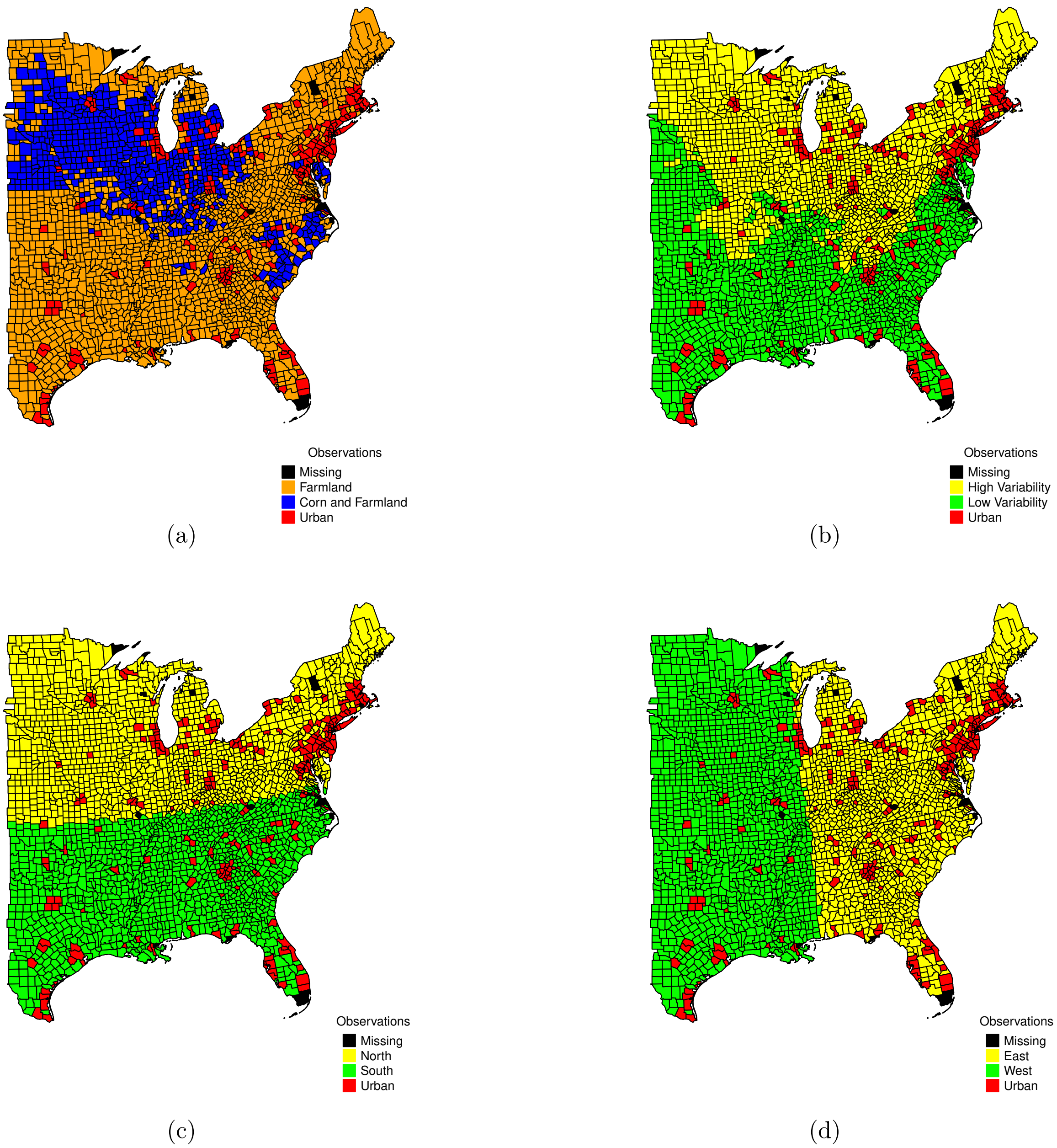
It is widely known that a majority of U.S. crops require at least 20 inches of water a year to grow. In the contiguous United States, a distinctive geographic boundary exists to delineate regions that do and do not receive this minimum requirement: the 100th meridian. Commonly referred to as the "rainline", agriculture is able to occur without supplementary irrigation water to the right (east), whereas to the west (left) it generally cannot. Hence, the usage of irrigated water for farming operations severs the direct connection between that farmer's current climate, specifically precipitation and temperature, and farm-level economic outcome.

Figure 2 displays a map of the study's sample area, where counties in the contiguous United States were omitted if they can be classified to be irrigated or urban. This panel of data consists of county level observations in the contiguous United States from 1950 to 2012.

All monetary values are expressed in constant 2012 United States Dollars (USD) using the GDP implicit price deflator. A brief overview of the three families of data types – weather and climate, agricultural, and socio-economic – is discussed.

Weather and Climate Data

The weather and climate data come from two sources. The primary dataset is from Schlenker and Roberts (2009), and consists of interpolated monthly mean, maximum, and minimum temperature and precipitation amounts for 2.5×2.5 - mile grid cells across the contiguous United States from 1950 to 2005. The climate and weather data for the remaining



Notes: Figure a identifies the parent dataset. Farmland counties are the combined orange and blue counties, and is a panel of N=2,193 and T=14. The corn counties are in blue, with N=631 and T=63. Figure b corresponds to the geographic division of areas into high and low climate variability, based on the Coefficient of Variation for Degree Days $> 30°C$. Figure c shows the geographic subsamples into North-South divisions, and Figure d, the East-West divisions. Counties in red are urban, while counties in black are missing.

Figure 2: Parent Dataset and Regional Divisions

years of this study (2006-2012) are from PRISM. The PRISM data is aggregated to the county level in order to match with agricultural areas.[12]

[12]Special thanks to Ortiz-Bobea (2016) who accomplishes this task by weighting each native PRISM grid by the amount of cropland it contains based on the USDA Cropland Data Layer. The Cropland Data Layer

Socio-economic

County level population data comes from both the United States Census and Intercensal Estimates. However, these data are only available between 1970 and 2012. Consequently, the remaining population data is obtained from Haines, Fishback, and Rhodes (2012). Because intercensal estimates before 1970 are not available, county populations for study years are interpolated between decennial censuses using a natural spline.

Agricultural

The agricultural data for this study come from two sources: Haines, Fishback, and Rhode (2012), and the United States Department of Agriculture National Agricultural Statistics Service. The data from Haines, Fishback and Rhodes (2012), is a collection of US Census of Agriculture data, whereas the NASS data used in this study consists of a 63 - year panel (1950 - 2012) of corn yields.

The USDA Agricultural Census dataset provides a comprehensive overview of the number, types, output, and prices of various agricultural products, as well as information on the amount, expenses, sales, values, and production of machinery. The surveyed population are operators of farms and ranches who have sold at least $1,000 of agricultural products during that census year.

There are a total of fourteen agricultural censuses (beginning with the 1950 and ending with the 2012 agricultural census) included in this analysis. The number of eastern non-urban counties with non-missing farmland data is equal to 2,193 for all census years.

Dependent Variable

The primary dependent variable used in this study is the value of land and buildings (USD per acre), which is obtained by asking farmers their estimate of the current market value of their land and buildings. Like MNS (1994), I interpret the value of land and buildings to be

(CDL) provides 30-meter resolution land cover pixels, which correspond to over 100 land classifications. The weights are based on cropland pixel counts falling within each PRISM data grid. The average of the CDL cropland counts for years 2008-2014 were used.

a proxy of farmland value.

Independent Variables

Agronomists have shown that plant growth depends on the cumulative exposure to heat and precipitation during the growing season (Deschênes and Greenstone, 2007). There is a threshold of temperatures - an upper and lower bounds - which crops can absorb heat and benefit. Exceeding this upper bound has adverse impacts on both the crop's yield and health. I follow the standard method to capture this nonlinearity by utilizing degree days: the amount of time a crop spends between its upper and lower bounds.

Degree days are typically assigned to one of two categories: normal degree days (which fall between the range of that crop's upper and lower bounds), and harmful degree days, temperatures which exceed the upper bounds. Given that the upper thresholds for the three most important cash crops of corn,soy, and cotton have upper temperature bounds of 29°C, 30°C, and 32°C, two common combinations of degree day assignments are 1) degree days $10-30°C$ with harmful degree days equal to above 30°C, and 2) degree days $8-32°C$ and harmful degree days of degree days above 32°C. I test the sensitivity of the temperature effect on land value by employing both of these alternative degree day specifications.

Auffhammer et al.(2013) emphasize that because precipitation and temperature are often correlated, the coefficient on precipitation will measure the combined effect of the two weather variables on a model's dependent variable. In order to obtain unbiased estimates of the marginal effects of precipitation and temperature on farmland values, growing season precipitation and quadratic growing season precipitation are included as independent variables.

Summary Statistics

Table 1 provides a snapshot of our panel of data, highlighting the summary statistics of agricultural and weather variables.

Table 1: Agricultural and Climate Variable Summary Statistics

Variable	μ	min	max	σ
Farmland Value	1,755.35	50.39	21,807.05	1,325.92
Farmland Acres	240.38	0	217.6	181.5
Degree Days $8-32°C$	2,192.43	928.4	3,160.65	349.62
Degree Days $10-30°C$	1,652.06	686.5	2,234.35	230.69
Degree Days $> 30°C$	70.43	0	498.62	66.82
Degree Days $> 32°C$	31.36	0	325.8	39.2
Precipitation	581.52	166.44	1,398.75	149.74

Notes: Values are county averages of a balanced farmland panel, where N=2,193 and T=14, east of the 100^{th} meridian. Counties were omitted if their population density was greater than 400 persons per square mile. The growing season is April through September. Farmland Value is reported in constant 2012 USD, Farmland Acres are in thousands of acres, and Precipitation is reported in millimeters.

Empirical Approach

To detect if weather shocks in the United States have been capitalized into the farmland market, I employ two models utilizing weather variation in a panel data setting across time to estimate the sensitivity of weather effects on farmland value. A distinctive advantage of using a panel method is that year-to-year variations in weather are plausibly random to farmers.

The first model is a simple OLS regression that exploits random variation in yearly weather observations is as follows:

$$y_{it} = \alpha_i + \tau_t + z_{it} + p_{it} + p_{it}^2 + \epsilon_{st} \tag{4}$$

where y_{it}, is the natural log of farmland value for a county i in time period t. The terms α_i and τ_t represent county effect and time effects, respectively. Whereas the county effect will absorb any fixed spatial, time-invariant characteristics (such as soil quality), the time effect will neutralize any common shocks and thus help ensure that relationships of interest are identified from idiosyncratic local shocks. It should be noted that while year and location fixed effects may capture all time-invariant and time-varying confounding factors, a large amount of variation is also captured and hence amplifies measurement error. The error term ϵ_{st} , corrects for spatial correlation by clustering standard errors by state and year. The term z_{it} represents temperature realizations while the two terms p_{it} and p_{it}^2 represent precipitation and quadratic precipitation for the growing season. Auffhammer et al.(2013) emphasize that because precipitation and temperature are often correlated, the coefficient on precipitation will measure the combined effect of the two weather variables on a model's dependent variable. Hence, in order to obtain unbiased estimates of marginal effects of precipitation and temperature on farmland value, both must be include in our regression.

Without the inclusion of lagged weather variables, one might incorrectly conclude that a regression's outcome is a permanent effect instead of a transient one. To investigate if the baseline model's results represent permanent or temporary effects, a finite distributed lag model is estimated where:

$$y_{it} = \alpha_i + \tau_t + \sum_{n=0}^{n=N} \beta_n X'_{i,t-n} + \epsilon_{st} \tag{5}$$

where y_{it} represents the value of agricultural land per acre in county i for year t. The term $X'_{i,t-n}$ is a vector of temperature and quadratic precipitation realizations. The term α_i represents a full set of county fixed effects, whereas the term τ_t identifies the year effect. Notice the n subscript for the $X'_{i,t-n}$ vector, where $n{=}N$ represents the total number of lags considered. By looking at a number of lagged weather variables, we can determine if changes in farmland value over time is a function of current and past weather events $X'_{it}, X'_{i,t-1}, ...X'_{i,t-n}$, where the last term $X'_{i,t-n}$ indicates that after N lags, the effect of previous weather events on current land and building values has been exhausted. It is often a concern that X'_{it} and $X'_{i,t-1}$, along with all other pairs of lags will be highly collinear. However, because weather fluctuations are considered random at a specific location, and tend not to be serially correlated in consecutive years, I believe the concern of collinearity is mitigated. This is assuming that the number of lags have been correctly specified. If they have been misspecified, then the lag distribution will be inaccurate and the cumulative impact of Degree Days on land values will be biased.[13] The exhaustion of this effect is econometrically tested through a joint-hypothesis F-test, whereby if $\sum_{n=0}^{N} \beta_0+\beta_1+...\beta_N \neq 0$, the effect is a permanent, as opposed to a transitory one.

Stability

In addition to the baseline and distributed lag model, I investigate the sensitivity of the temperature-farmland value relationship across time and space through a series of robustness checks. The intuition of comparing empirical results by stratifying observations on temporal and geographic divisions, such as years and geographic coordinates, allows the researcher to investigate if the overall regression results are uniformly experienced or if particular subsets experience different marginal impacts. This is achieved by conducting a Wald test to determine whether all coefficients for subgroups are jointly the same.

Stability Over Space

To examine the sensitivity of the temperature effect on farmland, I adopt two methods to spatially separate the study area. The first method divides the sample into two equally sized, and mutually exclusive regions of East and West or North and South, using the study's median latitude and longitude observations to segment the regions. Recall the theoretical assertion that all things considered, a farmer with a more variable baseline climate, will update their beliefs of climate norms more slowly than a farmer who has a less variable baseline climate. To reflect this hypothesis, the second division is made by separating counties based on the coefficient of variation for harmful degree days.

Stability Over Time

The premise that there has been a shift in the farmer's belief about climate change over the last thirty years is an empirical foundation that Severen et al.(2016) promote. However, whereas the authors examine the evolution of climate change beliefs in the cross-section, I am motivated to examine this relationship with a panel model, and to see if there has been a structural shift in the farmland market. To that extent, I divide the sample into two

[13]Following the literature, I choose to determine lag length by sequentially adding lagged weather variables until the latest addition is no longer statistically significant.

equally-sized year groups of 1950 - 1978 and 1982 - 2012.

Empirical Results

The main set of regressions in this study utilize the tandem of normal degree days with upper and lower thresholds of degree days $10-29°C$ and harmful degree days as the aggregate of degree days over 30°C.

The OLS results of (4) are compared to a pooled OLS model in Table 2. An F-Test confirms that (4) performs better than the pooled OLS alternative.[14] Regardless of the inclusion or omission of fixed effects, none of the four weather variables are distinguishably different from zero.[15] Two sets of standard errors are located under each regression coefficient. The naive standard errors are in parentheses, and have not been corrected for heteroskedasticity or spatial correlation. In brackets, are multiway clustered errors at the state and year level. This latter set corrects for heteroskedasticity and spatial correlation. All subsequent models in this analysis include fixed effects and multiway clustered errors, unless stated else wise.

Stability Across Space

Division into Cardinal Directions

To verify if the effect of these weather fluctuations on changes in farmland value are stable across space, I first divide my study area into cardinal directions of East, North, South, and West, and re-estimate the baseline line model. Separation into these four regions was motivated by the clear trend in temperatures cooling from south to north, and a markedly distinct pattern in increasing growing precipitation from West to East, as evidenced in Figure 3, which illustrate regional differences in exposure to Degree Days > 30°C and growing season precipitation.

Table 3 presents the results of the baseline regression when we include an interaction of a regional dummy with the four weather variables. In Column A, (4) is interacted with regional dummy East-West, whereas in Column B, our baseline model is interacted with

[14]Performs better refers to the fact that the pooled OLS estimates will be biased. The F statistic was 6.6985 with $p < 2.2e^{-16}$.

[15]Though it is worth noting that with exception to Harmful Degree Days, the signs on the weather coefficients between these two models, are opposite.

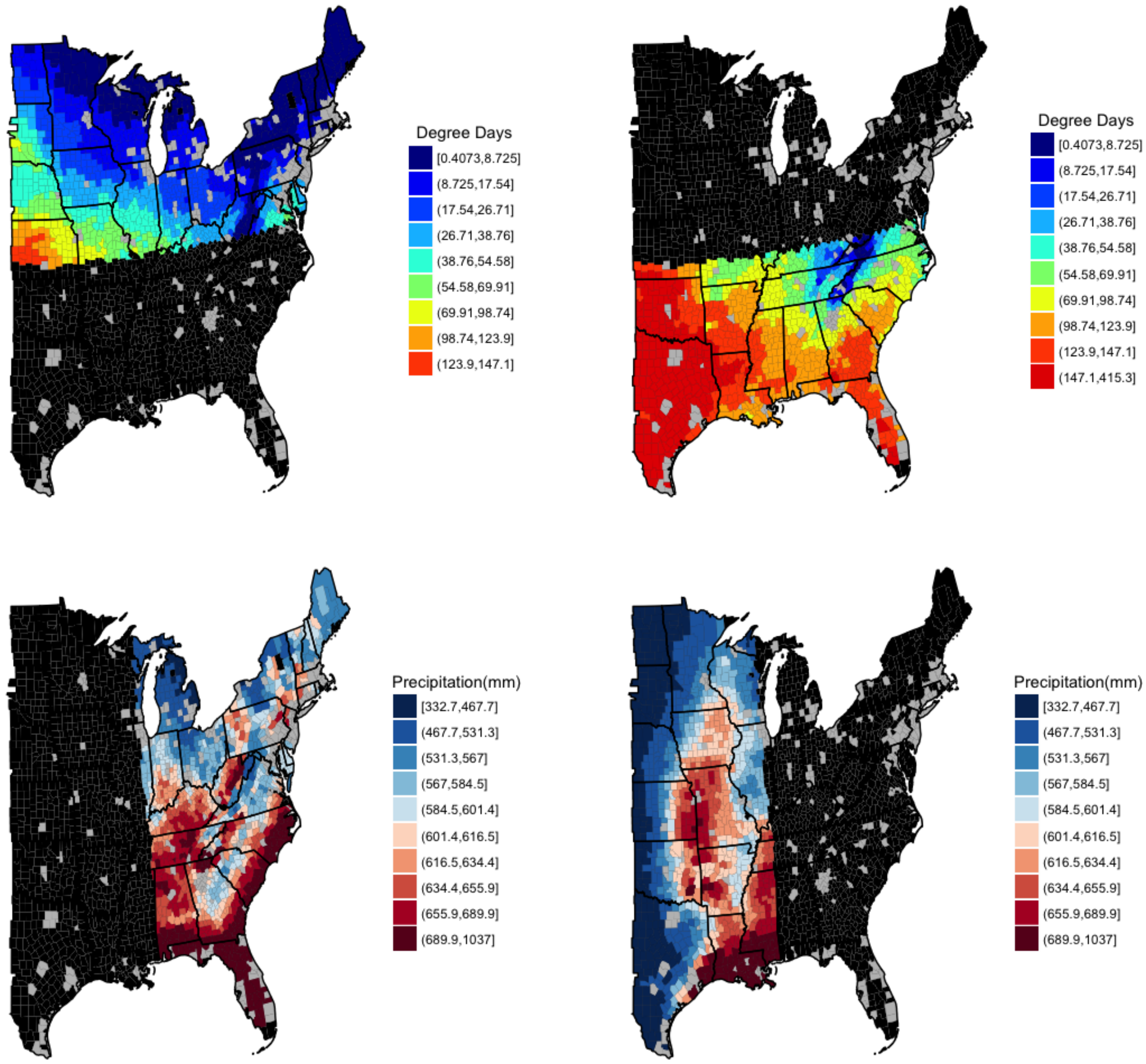
Table 2: Baseline Regression Results With and Without Fixed Effects

	Model	
	Fixed Effects	No Fixed Effects
Degree Days $10-30°C$	-25.92	91.08
	(2.94)	(2.44)
	[37.28]	[28.71]
Degree Days $> 30°$C	-20.86	-382.50
	(8.09)	(7.87)
	[94.10]	[99.60]
Precipitation	8.22	-165.15
	(4.08)	(9.80)
	[25.92]	[130.45]
Precipitation^2	-0.03	0.37
	(0.01)	(0.03)
	[0.08]	[0.38]
Observations	30,702	30,702
R^2	0.0034	0.0789

Notes: The above table corresponds to a model for panel data of farmland values, where N = 2,193 and T = 14 census years (1950-2012). There are two sets of standard errors reported under the regression coefficient. The untreated, naive standard errors are in parentheses. In brackets are standard errors which have been clustered by state and year. The left-hand panel represents our baseline model with county and year fixed effects. The right-hand panel represents our baseline model when fixed effects are omitted. Statistical significance is reported at $\alpha = 0.1^{*}, \alpha = 0.05^{**}, \alpha = 0.01^{***}$, respectively. To interpret coefficients and standard errors, the reader should divide the entry of interest by 100,000.

regional dummy North-South. As evidenced in Column B, the baseline model results appear to be sensitive to regional divisions, whereby, while no weather variables are statistically indistinguishable from zero in Column A, both precipitation terms for the southern region are highly significant, and with the expected sign in Column B. Additionally, the R^2 terms in both models has significantly increased from the baseline comparison: rising from 0.003 to 0.021 in the North-South regression, and 0.011 in the East-West regression.

A possible explanation as to why the weather coefficients are not jointly different in the East-West separation could be attributed in part to the comparatively similar temperature exposures, in comparison to the North-South division. While temperature has often been attributed as the stronger of the two drivers in climate change, and given that the noticeable difference in East-West is precipitation, it could be that because there is relatively more irrigated land in the western half of the sample, hence the two regions experience the same



Notes: These figures correspond to harmful degree days (Degree Days $> 30°$C) and growing season precipitation in the bottom panes over the growing season April - September, when the panel of farmland data is split into equally sized regions where $N = 549$ (North,South) and N=*548* (East,West) counties. Note that these are average exposures per year. Counties that are shaded in *grey* correspond to missing counties. Counties shade in *black* correspond to counties that are not in that particular region.

Figure 3: Degree Days $> 30°$C and Growing Season Precipitation Across Cardinal Regions

effect of weather shocks on changes in farmland value. Alternatively, because precipitation events tend to occur on a smaller spatial scale than are generally measured, there is higher likelihood that this weather variable is suffering from measurement error.

Table 3: Baseline Regression Results by Cardinal Direction

	A		B	
	East	West	North	South
Degree Days $10-30°C$	−25.43 [37.42]	−43.99 [46.39]	−21.55 [38.91]	−30.91 [38.33]
Degree Days > 30°C	−171.40 [156.84]	−6.80 [115.67]	−145.57 [148.42]	−103.88 [86.74]
Precipitation	−19.40 [42.42]	24.06 [30.90]	70.58 [48.10]	−58.68*** [15.78]
Precipitation^2	0.000,2 [0.11]	−0.03 [0.10]	−0.20 [0.19]	0.14*** [0.03]
Wald Test of Joint Significance (p-value)	0.392	0.392	0.001***	0.001***
Number of Weather Variables Individually Different at p=0.05	1	1	3	3
Observations	15,351	15,351	15,351	15,351
R^2	0.01143	0.01143	0.02084	0.02084

Notes: The above table corresponds to the baseline model when divided into regions of East versus West, and North *versus* South. In brackets are standard errors which have been clustered by state and year. The number of weather variables across regional pairings is reported on the last line. A value of 3 indicates that 3 out of the 4 weather variables were individually different at the $p = 0.05$ level. Statistical significance is reported at $\alpha = 0.1^{*}, \alpha = 0.05^{**}, \alpha = 0.01^{***}$, respectively. To interpret coefficients and standard errors, the reader should divide the entry of interest by 100,000.

Division into High and Low Climate Variability

This study's interest in examining if farmers are capitalizing expectations of recent weather shocks can be dissected even finer: of chief interest is the modeling and understanding how this group of stakeholders reacts to harmful degree days. Instead of dividing the sample into groups based on their geographical location, I separate the study area into different regions based on the variability of a climate variable: harmful degree days. To model this climate variability, I elect to calculate the coefficient of variation for the aforementioned variable, which is the ratio of the standard deviation to the mean. This calculation allows us to map the yearly fluctuation in harmful degree days, and has a straightforward interpretation: the higher the coefficient of variation, the larger the yearly fluctuations in the variable of interest, which translates into a less stable and less predictable climate.

Table 4 presents the result of the baseline regression model when the weather variables are interacted with a coefficient of variation for harmful degree days dummy. Linear and quadratic precipitation terms are statistically significant and have the expected sign. How-

Table 4: Baseline Regression Results by Climate Variability

	Climate Variability	
	High	Low
Degree Days $10 - 30°C$	-14.62	-48.25*
	[38.26]	[34.36]
Degree Days > 30°C	17.68	-71.81
	[92.56]	[90.73]
Precipitation	68.22**	-23.70
	[36.59]	[23.96]
Precipitation^2	-0.26**	0.08
	[0.13]	[0.05]
Wald Test of Joint Significance (p-value)	0.002**	0.002**
Number of Weather Variables Individually Different at p=0.05	3	3
Observations	15,351	15,351
R^2	0.01003	0.01003

Notes: The above table corresponds to the baseline model when divided into regions of high and low climate variability for CV of harmful degree days. In brackets are standard errors which have been clustered by state and year. Statistical significance is reported at $\alpha = 0.1^{*}, \alpha = 0.05^{**}, \alpha = 0.01^{***}$, respectively. To interpret coefficients and standard errors, the reader should divide the entry of interest by 100,000.

ever, whereas these terms were statistically significant in the Southern region in Table 3, they are now statistically significant for the less stable. A single weather variable, normal degree days, is statistically significant in the more stable region. A Wald test rejects the null hypothesis that the weather coefficients for these two regions are jointly the same, which provides supporting, though not absolute, evidence that how variable of a climate a farmer lives in plays a role in their capitalization of weather shocks.

Testing Across Time

Table 5 highlights that no weather variables across time are statistically indistinguishable from zero. A Wald test for joint significance concludes that these two subsamples of time are not jointly different from each other, and all pairwise tests of equality fail to reject the null hypothesis that they are equal.

As a side note: it would be interesting to take this finding and investigate if, when I introduce climate variables in an alternative model, those results support those of Severen

Table 5: Baseline Regression Results Across Two Time Periods

	Time Period	
	Early	Late
Degree Days $10-30°C$	−27.49	−26.45
	[35.88]	[36.51]
Degree Days > 30°C	−28.35	−29.79
	[88.90]	[90.85]
Precipitation	−20.88	34.40
	[33.87]	[45.19]
Precipitation^2	0.06	−0.09
	[0.13]	[0.12]
Wald Test of Joint Significance (p-value)	0.794	0.794
Number of Weather Variables Individually Different at p=0.05	0	0
Observations	30,702	30,702
R^2	0.0076	0.0076

Notes: The above table corresponds to the baseline model when divided two equal subsets of time. The panel labelled Early is for the panel of data from 1950-1978, while the right-hand panel, labelled Late epresents census years 1982-2012. In brackets are standard errors which have been clustered by state and year. Statistical significance is reported at $\alpha = 0.1^{*}, \alpha = 0.05^{**}, \alpha = 0.01^{***}$, respectively. To interpret coefficients and standard errors, the reader should divide the entry of interest by 100,000.

et al.(2016), who have concluded that since 1987, there has been a structural shift in the farmland market and farmers are capitalizing their beliefs of climate change.

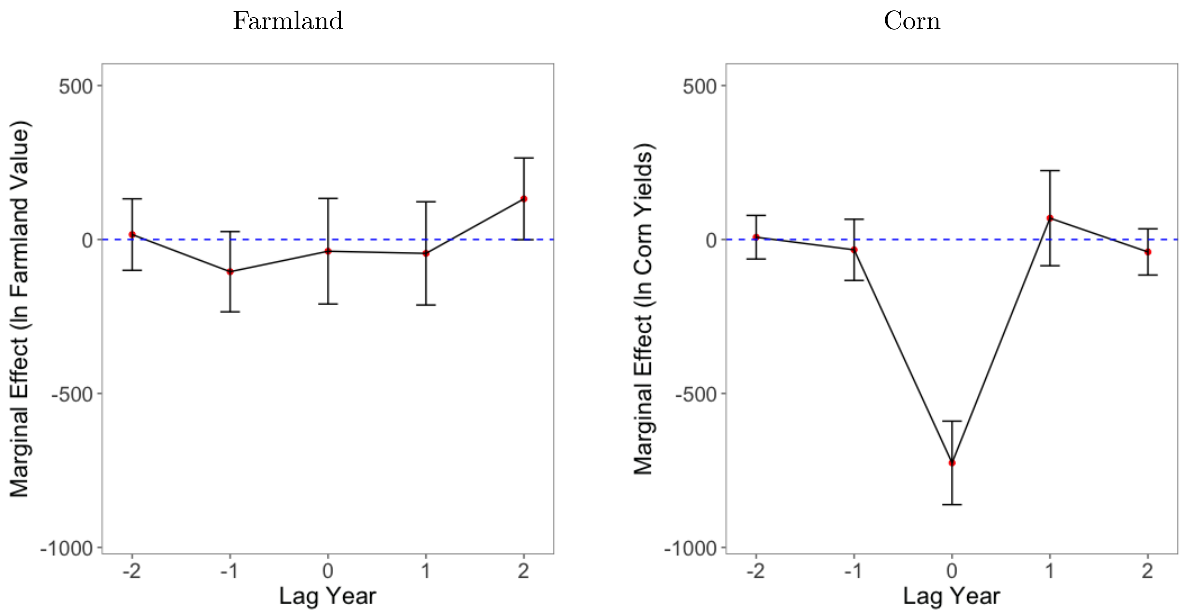
Distributed Lag Model

Thus far, the narrative of my empirical results reflects weather shocks and changes in farmland value over current weather for each census year. This implicitly assumes that, for each respective census year, farmers did not consider past or future weather events to play any role in their future expectations of farmland value. In the author's opinion, this is too strong of an assumption to make, and therefore I conduct a distributed lag model that includes lags (past) and leads (future) of weather. Ample research has been done in agricultural economics to show that corn yields are only impacted by current weather realizations, are not affected by future or past weather events (Hsiang, 2016).

In Figure 4, the left-hand panel highlights the relationship of interest between farmland values and harmful degree days. I find that neither contemporaneous, future, or past harmful degree days are indistinguishably different from zero. In contrast, the right-hand panel illustrates that only contemporaneous harmful degree days affects the variance in corn yields.

This is a solid falsification test, and reassures us that the weather variables being used are of good quality. Table 6 shows the evolution of the baseline model's weather variables over different lags and leads.

To identify if these weather shocks have a permanent or transitory effect on farmland values, I conduct an F-Test that the cumulative effect of each weather variable's lagged terms are jointly equal to zero. With an F-stat of 0.5543 and a corresponding p-value of 0.6959, I fail to reject the null hypothesis that these weather shocks have a temporary effect on the farmland market, and confirm that it is not a permanent one.



Notes: These figures correspond to the marginal effects of harmful degree days, Degree Days 30°C for natural log of farmland value (left) and natural log of corn yields (right). While only contemporaneous harmful degree days explains variations in corn yields, we cannot detect any explanatory power for periods of harmful degree days in terms of explaining variation in farmland value. To interpret these standard errors, the readers should divide the value by 100,000.

Figure 4: Marginal Effects of Lags and Leads For Two Dependent Variables

Robustness Checks

The findings thus far have all been based on the usage of one set of temperature variables - Degree Days $10-30°C$ and Degree Days $>$ 30°C - and one growing season, April to September. As a final series of robustness checks, I test the sensitivity of my findings by: 1)Using an alternative set of temperature variables, Degree Days $8-32°C$ and

Table 6: Baseline Regression Results Across Two Time Periods

	Lag Year				
	-2	-1	0	1	2
Degree Days $10-30°C$	-24.73	-24.72	-25.92	-25.67	-24.37
	[35.88]	[35.65]	[37.28]	[30.31]	[27.65]
Degree Days > 30°C	-5.11	-1.60	-20.86	-20.89	-53.56
	[101.76]	[101.99]	[94.10]	[83.13]	[80.54]
Precipitation	9.23	9.35	8.22	8.06	8.72
	[22.57]	[24.03]	[25.92]	[25.55]	[24.37]
Precipitation^2	-0.03	-0.03	-0.03	-0.03	-0.03
	[0.07]	[0.07]	[0.08]	[0.07]	[0.10]
Degree Days $10-30°C$ lag1	-3.78	4.64			
	[28.66]	[21.49]			
Degree Days $10-30°C$ lag2	22.48				
	[24.44]				
Degree Days > 30°C lag1	-81.03	-83.16			
	[76.11]	[77.83]			
Degree Days > 30°C lag2	-14.65				
	[54.23]				
Precipitation lag1	-33.43	-35.07			
	[24.09]	[23.73]			
Precipitation lag2	-16.62				
	[27.69]				
Precipitation^2 lag1	0.03	0.03			
	[0.06]	[0.06]			
Precipitation^2 lag2	0.03				
	[0.08]				
Degree Days $10-30°C$ lead1				0.51	-19.47
				[19.68]	[26.62]
Degree Days > 30°C lead1				5.10	-50.22
				[80.67]	[]
Precipitation lead1				5.47	-3.09
				[25.48]	[22.00]
Precipitation^2 lead1				-0.01	0.01
				[0.07]	[0.14]
Degree Days $10-30°C$ lead2					43.81*
					[25.49]
Degree Days > 30°C lead2					130.96*
					[73.44]
Precipitation lead2					-5.03
					[18.54]
Precipitation^2 lead2					0.09
					[0.08]
Observations	30,701	30,701	30,702	30,701	30,701
R^2	0.0213	0.0165	0.0034	0.0038	0.0239

Notes: The above table corresponds to regression results for farmland value from 1950-2012 with different lag(past) and leads(future) of weather variables.The left-most column, with a lag of -2, stands for weather two years prior the agricultural census. Whereas the column with lag 0 represents contemporaneous weather. Note that the right-most column has a lag of 2, indicating weather two years after each census. Standard errors are reported below coefficients, in brackets, and are clustered by state and year. Statistical significance is reported at $\alpha = 0.1^{*}, \alpha = 0.05^{**}, \alpha = 0.01^{***}$, respectively. To interpret coefficients and standard errors, the reader should divide the entry of interest by 100,000.

Degree Days >32°C , but do not change the growing season and 2) Using an alternative start and end of the growing season of March to August, with Degree Days$10 - 30°C$ and Degree Days > 30°C.[16]

The inability to distinguish any of the four weather variables from zero in our baseline model is stable when the sample is split into sub groupings of study years for alternative growing seasons and weather variables. That we find less stability across space across these alternatives, is not that surprising and exemplifies that spatial heterogeneity is a very potent presence in farmland value and weather observations. Results from the placebo test conducted in the distributed lag model confirms that recent weather shocks have had a transient impact on changes in farmland values, as opposed to a permanent one.

Conclusion

With the growing likelihood that accumulating greenhouse gases will change the impact climate, there has been growing interest in also measuring the impact of climate change on agriculture. Currently, agriculture is arguably one of the most researched sectors in the climate change impacts literature. In this study I combine elements of the Ricardian approach and panel approach to analyze the effects of weather shocks on the farmland market. Moreover, because these yearly fluctuations in weather are essentially random and independent of other unobserved determinants of agricultural outcomes, these panel estimates correct for omitted variable bias.

The overarching goal of this paper has been to conceptualize, explore, and calculate if recent weather shocks have been capitalized by farmers, in the form of changes in farmland value. This was accomplished in three stages. Specifically, I examined if the impacts of of weathers shocks on farmland value is stable across time and space sub groupings. I also divided the sample into regions that are identified as having more and less stable climates, and

[16]The correlation coefficient between the Degree Days$10-30°C$ and Degree Days$8-32°C$ is 0.981, while the correlation coefficient between harmful degree day alternatives of Degree Days > 30°C and Degree Days > 32°C is 0.978, confirming that interchanging the pair of degree day terms will pick up the same signal in changes of farmland value. Similarly, when we change the seasons, the correlation coefficient for Degree Days > 30°C between the two seasons is 0.962, while the correlation coefficient for Degree Days $10 - 30$°C is 0.996. The correlation coefficient for growing season precipitation is 0.913.

examined if the farmer with a less stable climate is more likely to capitalize an idiosyncratic weather shock. And lastly, I examine if farmers are forward looking or myopic through a distributed lag model.

This body of research is an extension of the increasingly popular method to frame farmers as forward thinking and not myopic. In contrast to focusing on survey data that represents an amalgam of public opinion and agricultural surveys, I restrict data observations to the stakeholder of interest, the farmers, and base identification upon how farmland values changes with weather realizations.

That I was unable to distinguishably conclude that any of my weather parameters were different from zero prompted a further exploration across regional and temporal subsets, upon which I conclude that while my findings are robust across time, they are notably sensitive when divided by geographical location. One alternative explanation to why we may not have found temporal differences in the effects of weather shocks is the fact that farmers within each state have adapted to climate change at different rates. So while it is likely that individually, states have different tolerances of weather shocks, across the two designated sub periods, it was relatively equal.

The decision to measure if weather shocks have the same effect on changes in farmland values, when farmers are split into regions of more and less climate stability, pairs nicely with our theoretical model. Such a division into more and less stable climates allows us to test the hypothesis that all else equal, the updating of a farmer's prior beliefs of the mean weather will be driven by the variability of weather (variance in weather realizations). However, caution should be taken when interpreting these results. Though I find stable results across alternative growing seasons and harmful degree day cut offs, that I do not acknowledge that these regions have uniquely different temperature thresholds is an important one. I cannot rule out that degree days are an overly restrictive functional form for this model. As such, future research would benefit by modeling the temperature effect on changes in land value in a more flexible form and utilize the entire distribution of weather, avoiding the issue of assigning temperatures as harmful and beneficial.

Perhaps the most promising piece of empirical results coming out of this study are the fact that I found convincing evidence that neither past, present, or future weather weather shocks are being capitalized by farmers in the farmland market. As a check, I find evidence supporting the intuition and previous research that corn yields are only impacted by current weather and not future or past weather, as is evidenced in Figure 4. Such a check helps reduce, though does not cancel out, the probability that the empirical results are spurious.

There are a number of important caveats which my analysis has not yet incorporated and warrant addressing. Firstly, the issue of utilizing fixed effects. A powerful advantage of time and location fixed effects includes the ability to capture all time-invariant and time-varying confounding factors, respectfully. However, by including both year and fixed effects, a large amount of variation is also captured and hence amplifies measurement error. As such, further research should explore the usage of alternative panel methods, such as the usage of a spatial lag model. A second caveat relates to the issue of government payments. As aforementioned in the Introduction, it is unclear if farmers undertake costly adaptation strategies to cope with a changing climate, when there is a history of the governmental agriculture support programs protecting farmers against substantial losses.

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